Targeting Conservation Investments
in Heterogeneous Landscapes:
A distance function approach and
application to watershed management

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Abstract

To achieve a given level of an environmental amenity at least cost, decision-makers must integrate information about spatially variable biophysical and economic conditions. Although the biophysical attributes that contribute to supplying an environmental amenity are often known, the way in which these attributes interact to produce the amenity is often unknown. Given the difficulty in converting multiple attributes into a unidimensional physical measure of an environmental amenity (e.g., habitat quality), analyses in the academic literature tend to use a single biophysical attribute as a proxy for the environmental amenity (e.g., species richness). A narrow focus on a single attribute, however, fails to consider the full range of biophysical attributes that are critical to the supply of an environmental amenity. Drawing on the production efficiency literature, we introduce an alternative conservation targeting approach that relies on distance functions to cost-efficiently allocate conservation funds across a spatially heterogeneous landscape. An approach based on distance functions has the advantage of not requiring a parametric specification of the amenity function (or cost function), but rather only requiring that the decision-maker identify important biophysical and economic attributes. We apply the distance-function approach empirically to an increasingly common, but little studied, conservation initiative: conservation contracting for water quality objectives. The contract portfolios derived from the distance-function application have many desirable properties, including intuitive appeal, robust performance across plausible parametric amenity measures, and the generation of ranking measures that can be easily used by field practitioners in complex decision-making environments that cannot be completely modeled.

I. Introduction

Given the difficulty of measuring environmental benefits in currency, many economic analyses focus on achieving "efficiency without optimality" [Baumol and Oates 1988: 159]. To achieve a given level of an environmental amenity at least cost, decision-makers must integrate information about spatially variable biophysical and economic conditions. In the case of endangered species conservation, for example, previous analyses have focused on maximizing, subject to a budget constraint, biological diversity measures [Solow *et al.* 1993; Weitzman 1992, 1993, 1998], habitat priority indices [Balmford *et al.* 2000], or the total number of species conserved [Ando *et al.*, 1998; Montgomery 1995; Polasky and Solow 1995; Polasky *et al.* 1993, 2001]. In the case of the multi-billion dollar U.S. Conservation Reserve Program, Babcock *et al.* [1996, 1997] focused on separately maximizing individual proxies of environmental amenities. Other studies have looked at the allocation of scarce budgets in the cleanup of hazardous waste sites [Hamilton and Viscusi 1999; Viscusi and Hamilton 1999].

Most studies of cost-efficient conservation policy interventions have tended to use a single biophysical attribute (e.g., species absence or presence, genetic dissimilarity between species, erodibility of soil, distance to surface water) as a proxy for an environmental amenity. A narrow focus on a single attribute, however, fails to consider the full range of biophysical attributes that are critical to the supply of an environmental amenity [Noss 1990]. Most real-world conservation initiatives, like the U.S. Conservation Reserve Program [USDA 1999] or World Wildlife Fund's Global 200 initiative [Olson *et al.* 2000], identify multiple biophysical attributes (or amenities) of interest.

The use of a single biophysical attribute as a proxy for an environmental amenity is understandable given that scientists and practitioners often find it difficult to convert multiple biophysical attributes into a single environmental amenity measure. Parametric environmental amenity functions are usually absent or controversial. Although the biophysical attributes that contribute to supplying an environmental amenity like water quality are often known (e.g., riparian soil type, drainage area), the way in which these attributes interact to produce the amenity is often unknown.

Based on this observation, we introduce an approach that relies on distance functions to cost-efficiently allocate conservation funds across a spatially heterogeneous landscape. Distance functions allow one to describe a multi-input, multi-output production technologies without the need to specify a price vector (i.e., attribute weights) or a behavioral objective on the part of the production unit (in this case, a parcel of land). They have been used in economics for many decades [Shephard 1970], but have seen resurgence in recent years [e.g., Chambers *et al.* 1996, 1998; Chavas and Cox 1999; Färe and Grosskopf 1990, 1998, 2000; Lynch and Musser 2001]. An approach based on distance functions has the advantage of not requiring parametric specification of an amenity function (or a cost function). The approach only requires that the decision-maker identify important biophysical and economic attributes.

We apply the distance function approach empirically to an increasingly common, but little studied, conservation initiative: conservation contracting for water quality objectives. The contract portfolios derived from the distance-function application have many desirable properties, including intuitive appeal, robust performance across plausible parametric amenity measures, and the generation of ranking measures that can be easily used by field practitioners in complex decision-making environments that cannot be completely modeled. Although we focus on the case of multiple biophysical attributes, the approach easily generalizes to cases in which parametric amenity functions are known but a conservation agent is interested in multiple amenities (e.g., affecting land use to secure biodiversity *and* water quality benefits). Conner *et al.* [1995] have emphasized that a narrow focus on a single amenity can also lead to cost-inefficient interventions.

In the context of targeting habitat protection interventions, Prendergast *et al.* [1999] noted that field practitioners and policymakers rarely use the tools and results that have been developed in the academic literature. In large part, the tools and results are not adopted because they are not developed and applied with the objectives and approaches of practitioners and policymakers in mind. In the empirical application of this paper, we use data routinely available to decision-makers and consider explicitly the actual approaches used by decision-makers in the field. We also approach the problem at the geographic scale at which decisions are being made; i.e., individual parcels rather than large administrative districts or GIS polygons on the landscape.

In the next section, the conventional approach to targeting conservation investments is introduced. In section III, the alternative approach to targeting conservation investments using distance functions is presented. In section IV, the empirical case study is described and in section V, the results from this case are presented. In section VI, other aspects of the distance function approach are explored.

II. Conventional Approach to Targeting Conservation Investments

In the presentation of the conventional approach to targeting land conservation investments, we use the following notation:

p_i = Share of parcel i under conservation contract (p_i = 1 if parcel is fully contracted)

e_i = Environmental benefit from parcel i (a scalar; often an index value or a measure of a key objective, such as reduction in tons of sediment)

c_i = Contract cost for parcel *i* (private opportunity cost of conservation)

t_i = Transaction costs for a contract on parcel *i* (e.g., legal fees, monitoring)

D = Contracting agency's budget

As in previous analyses, we make several assumptions. First, each parcel can either generate net returns of c_i to the private landowner or environmental benefits of e_i to the contracting agent (and the citizens that it represents). Second, the unit of analysis is the parcel, and each parcel is assumed to be homogenous (heterogeneous parcels can be divided into homogenous sub-parcels, each with different values of *e* and *c*).

To identify the cost-efficient land portfolio that gives maximum environmental benefits per dollar expended, the decision-maker wants to solve

$$\max_{p_i} \sum_i p_i e_i \quad \text{s.t.} \qquad [1]$$

$$\sum_i p_i (c_i + t_i) \leq D \qquad [2]$$

$$0 \leq p_i \leq 1 \qquad [3]$$

This approach is the same as that used by Babcock *et al.* [1996; in Babcock *et al.*, e_i is either a measure of a single biophysical attribute or an index] and is similar in spirit to the approaches used in targeting investments for species conservation (the latter are often modeled as maximum coverage problems or as the maximization of a diversity measure subject to a budget constraint). Other characteristics of this approach are discussed in the appendix.

The degree to which a contracting agent can identify the "true" cost-efficient land portfolio via expressions [1]-[3] depends on the degree to which environmental benefits, e_i, are measured accurately.[1] Many conservation initiatives have multiple objectives. For example, in the empirical example of this paper, the City of Syracuse wishes to reduce sediment, chemical, pathogen and nutrient loading into its water supply. Even if the City were able to measure the way in which a conservation contract might decrease each of the pollutants on a particular parcel, the way in which the loadings of these pollutants combine to affect the main objective, drinking water quality, is unknown. As in the Syracuse case, field-level practitioners are generally not able to estimate pollutant loadings, much less how they interact to affect water quality. In most cases, decision-makers know only the biophysical attributes that contribute to the conservation objective.

In the Syracuse case, for example, a panel of scientists and policymakers has agreed that five biophysical attributes of riparian land are important in contributing to their policy objective, but the way in which the attributes combine to affect water quality is unknown (see Section IV). In order to estimate the benefits from an individual parcel, Syracuse policymakers have done what many conservation groups and academic scientists have done: they created a benefit index for each parcel based on its biophysical attributes. Such indices are most often constructed from weighted linear functions of the attributes or by assignment of points to each parcel based on its biophysical attributes or land uses. Scoring methods like these are quite common in the academic literature [e.g., Voogd 1983; Lemunyon and Gilbert 1993], in federal agency guidelines [e.g., USFWS 1982; Terrell *et al.* 1982; Allen 1983; McMahon 1983; Allen and Hoffman 1984; FDEP 1999], in water quality protection initiatives [e.g., Smith *et al.* 1995; Rowles and Sitlinger 1999; MDC 1999; FDEP 2000], and in the multi-billion dollar conservation

[1] We assume that contract cost uncertainty will eventually be resolved through negotiation or an auction-type mechanism. In circumstances without a mechanism for all landowners to reveal simultaneously their willingness-to-accept a contract, uncertainty over costs can make the *ex ante* targeting decisions difficult (i.e., with whom does one start negotiating?). We will argue that the distance function-based targeting approach offers advantages in such circumstances.

efforts of the U.S. Conservation Reserve Program [Feather *et al.* 1998], land trusts [e.g., The Nature Conservancy; Master 1991], international habitat protection groups [e.g., World Wildlife Fund; Olson *et al.* 2000], national wildlife protection initiatives [e.g., Partners in Flight; Carter *et al.* 1999], and farmland protection initiatives (e.g., American Farmland Trust).

Scoring functions, however, are highly subjective and may not capture decision-maker preferences very well. Psychological experiments and simple everyday experience indicate that identification of criteria weights is complicated even for experts [e.g., Narasimhan and Vickery 1988; Borcherding *et al.* 1993] and that simple linear preference functions can fail to capture actual decision-maker preferences [Keeney and Raiffa 1976]. As will be shown in the empirical example, there are often many plausible scoring functions for approximating environmental amenities. Uncertainty about the "true" value of e_i can make it difficult to choose the optimal land portfolio. In the next section, we draw from the literature in production efficiency analysis to develop an alternative cost-efficient targeting approach that does not depend on a parametric specification of an environmental amenity function.

III. Distance-Function Approach to Targeting Conservation Investments

In many conservation initiatives, the biophysical attributes that are important in contributing to the desired environmental amenity are largely agreed upon by practitioners and advising scientists. However, the way in which these attributes (e.g., riparian exposure, drainage area) combine to produce the desired objectives (e.g., reduced pathogen loading) is not simply a source of disagreement, but rather completely unknown in many circumstances. Instead of trying to approximate the environmental amenities from each parcel through a specific functional form, it may be more appropriate to target parcels based on their efficiency in "producing" the desired biophysical attributes. Such an approach is particularly reasonable in a conservation contracting initiative for water quality given that biophysical attributes have been shown to characterize well the underlying hydrological and ecological features of aquatic ecosystems [Jensen *et al.* 2001].

In any conservation contracting initiative, one wants to assess the desirability of contracting one parcel relative to contracting the other available parcels. To compare parcels, one can treat each parcel as a production unit that converts input -- the costs of conservation contracting -- into multiple joint outputs -- the parcel's biophysical attributes that contribute to the conservation goal. In such an approach to targeting, one is only concerned with the ability of a parcel to obtain maximal joint output given the cost of contracting for that parcel (one assumes that more of the desirable attributes is always better than less).[2]

The productivity of a parcel in producing the desired biophysical attributes given its contracting cost can be measured by an input distance function. A land attribute "production frontier" is estimated through nonparametric programming methods that place a linear, faceted conical hull (convex cone) over the observed land parcels in the input-output space, such that all parcels either lie on the surface of the cone or beneath it. Parcels can be ranked on relative cost-efficiency by considering a minimal reduction in the contract cost that, given the vector of parcel attributes, projects the parcel onto the efficient frontier. The piecewise-linear hull approach to frontier estimation was proposed in the 1950s by Farrell [1957], but did not become popular until programming methods were developed for multiple output-input cases [Charnes *et al.* 1978].

In the general case of K inputs and M outputs, we denote inputs by the non-negative vector $x = (x_1,x_2,\ldots,x_K) \in \Re_+^K$ and outputs by the non-negative vector $(y_1,y_2,\ldots,y_M) \in \Re_+^M$. In the

[2] If more information is known about the relative importance of each characteristic, that information can also be incorporated. See Section VI.

case of conservation contracting, inputs are the costs of conservation contracting (e.g., the contract payment, the monitoring cost),[3] and outputs are the desirable biophysical attributes secured by the contract for conservation (e.g., drainage area). We denote the input distance function as

$$D_I(x,y) = \max\{\rho : (x/\rho, y) \in S\} = (\min\{\rho : (\rho x, y) \in S\})^{-1}, \qquad [4]$$

where S is the "land attribute technology" that describes the transformation of contracting inputs into desirable land attributes; i.e., $S = \{(x,y) : x\, can\ produce\ y\}$. S is assumed to be a convex, closed set and inputs and outputs are freely disposable (outputs are disposable in the sense that partial parcel contracting is allowed).

The distance measure ρ is the factor by which all input quantities could be decreased while still remaining within the feasible input set for the given output level. The distance measure is (i) greater than or equal to one, (ii) equal to one if and only if a parcel belongs to the frontier, and (iii) non-decreasing in x and increasing in y. Shephard [1970] showed that the input distance function is the dual of the cost function.

The distance function defined by [4] can be estimated by mathematical programming methods. There are a variety of ways to specify the programming model, but all seek to use a subset of the N parcels to determine parts of the production frontier surface (normally constructed as piecewise linear).[4] To be efficient, a parcel vector must lie on this surface. Parcels not on the surface are termed inefficient and the input distance metric provides a

[3] If all costs are in dollar terms, the input vector has only one element. One can, however, define the vector more broadly to include costs about which a contracting agency is concerned but which cannot be easily converted into a dollar figure; for example, lost forestry jobs when old growth forest is protected from logging.
[4] In the operations research literature, methods that use Free Disposal Hull, Convex Hull, Stairwise Hull, and Convex Cone approaches often go under the name "Data Envelopment Analysis." The term was coined by Charnes *et al.* (1978), although others had proposed the method earlier (see Coelli *et al.* 1998 for references).

summary measure of the inefficiency, which, in the conservation contracting case, is the reduction in the contract cost required to put the parcel on the efficient frontier.

We use a piecewise-linear conical hull approach to estimate the distance function:

$$(D_I(x,y))^{-1} = \min_{\theta,\lambda} \theta \qquad [5]$$

$$st$$

$$-y_i + Y\lambda \geq 0 \qquad [6]$$

$$\theta x_i - X\lambda \geq 0 \qquad [7]$$

$$\lambda \geq 0 \qquad [8]$$

where θ is a scalar, λ is an Nx1 vector of constants, X is a KxN matrix of contract costs, and Y is an MxN matrix of biophysical attributes (or amenities, in the multiple-amenity context) . The value of θ obtained will be the efficiency score for the *i*-th parcel and corresponds to the inverse of the distance measure in [4]. By minimizing θ, one achieves maximal movement toward the frontier through a proportional reduction of inputs (i.e., radial contraction of the input vector). The contraction of the input vector, x_i, produces the projected point (Xλ,Yλ) on the frontier surface. This projected point is a linear combination of the observed data points. The constraints [6]-[8] ensure that the projected point cannot lie outside of the feasible production set. By construction, θ will be less than or equal to one, with a value of one indicating that the parcel is on the frontier. The program is solved N times, once for each parcel, thereby obtaining a value of θ for each parcel.[5]

The way in which the distance function ranks land parcels on the basis of productivity is illustrated in Figure 1, which depicts the simple case of one desired biophysical attribute. In the figure, the boundary of S is represented by the ray emanating from the origin and passing

[5] Most recent nonparametric programming applications that estimate production frontiers add an additional convexity constraint, $N1'\lambda = 1$, in order to allow for variable returns to scale (Coelli *et al.* 1998: 150). In the appendix, we explain why this convex hull approach is not appropriate for the case of targeting conservation investments.

through the parcel with coordinates (1, 2). The parcel at (1, 2) yields a distance measure of θ = 1 and is classified as "efficient." This parcel would be the most desirable for conservation contracting. The remaining parcels, which are not on the frontier, are classified as "inefficient" and yield a distance measure that indicates the minimal reduction in contract cost required to project the parcel onto the frontier. For example, the parcel with coordinates (4, 3.6) can be projected onto the frontier if its contract cost were reduced by a factor of (1-θ) = (1- 0.45) = 0.55, or $1.62. The projected point is therefore (1.98, 3.6), and θ = 0.45 indicates that the parcel is "45% of the way to the frontier." Parcels are ranked for acquisition from the highest value of θ to the lowest.

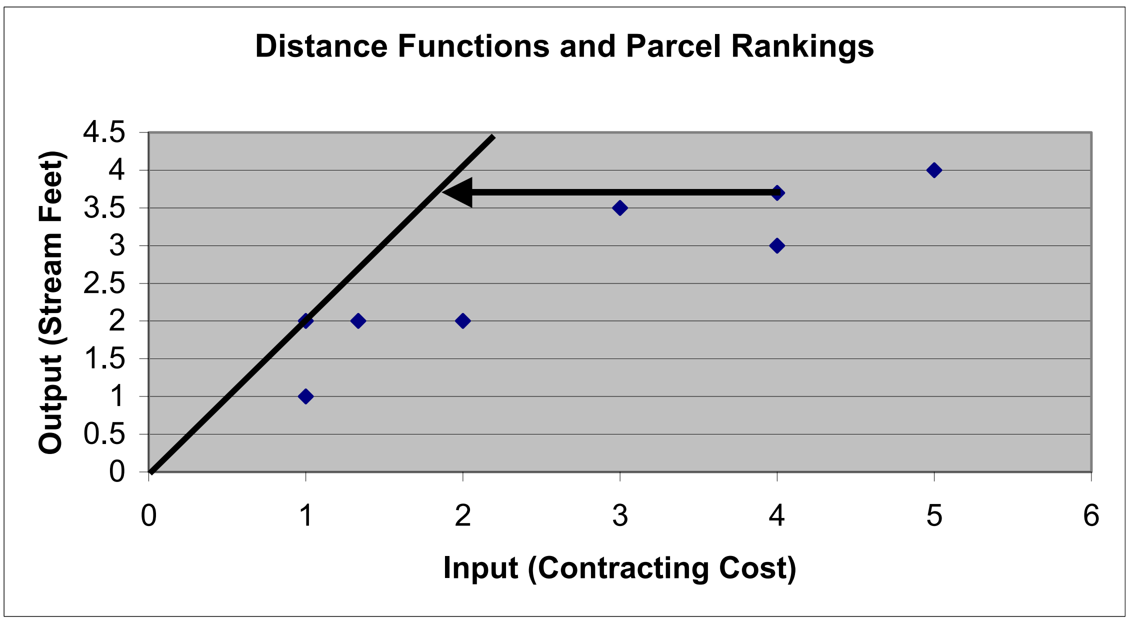

Figure 1. Distance Functions and Parcel Rankings

To understand how parcel acquisition priorities based on expressions [1]-[3] and [5]-[8] differ when e_i is an index constructed from a weighted linear equation of attributes, consider the case of one input, acquisition cost in dollars, and two biophysical attributes, *X* and *Y*. In order to present this case in two dimensions, we normalize the attributes to "attribute per dollar spent on acquisition." Figure 2 presents four parcels in the attribute space. The straight line through parcel A represents one possible weighting scheme in the linear scoring equation. With this scoring equation, parcel A is chosen first, parcel B second (the line is simply shifted down until it intersects with another parcel), parcel D third and parcel C fourth. Using (output) distance functions, a productivity frontier would be estimated (stylized by curved line) and parcels would be ranked depending on their distance from the frontier. In this case, parcel A and D would be considered equally as valuable, parcel B would be ranked third, and parcel C would be ranked fourth (the distance-function approach essentially allows the weights on each attribute to change across parcels, thereby allowing each parcel to be seen in its best light).

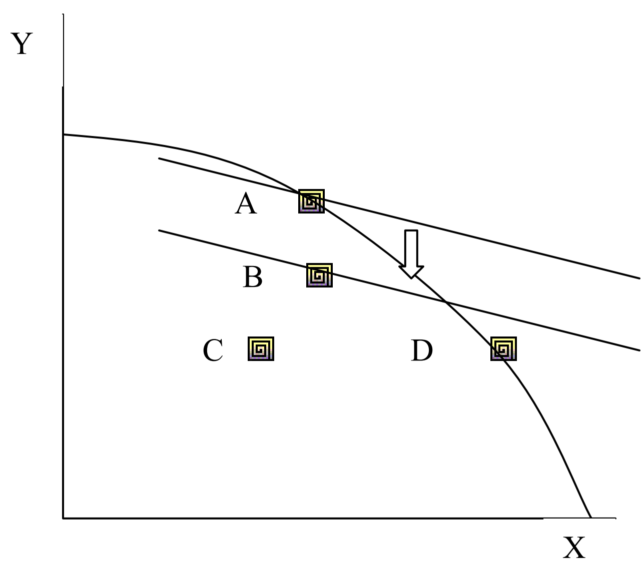

Figure 2. Weighted Linear Scoring Equations and Distance Functions Rankings

Unlike in the application of nonparametric programming and distance functions to the analysis of firm efficiency, the standard assumptions implied by the use of an input distance function and a nonparametric approach to estimating the frontier are not a problem in the conservation targeting context. First, the land attribute production technology characterized by the distance function is truly a joint production technology. Second, using a radial distance metric in input space, rather than a radial output metric or non-radial metric,[6] makes perfect sense in the context of conservation contracting because land attributes are not changeable; the only discretionary variable is the amount of money paid by the contracting agency.[7] By using an input-oriented metric, we also obtain an efficiency measure that is useful to a conservation agent that must negotiate with landowners: the distance function allows negotiators to evaluate the change in a parcel's relative ranking if the estimated contract cost changes during site visits and negotiation (see Section VI). A radial metric also has the desirable property that the efficiency measure is units invariant. In the next section, we describe the case study in which alternative targeting approaches are empirically evaluated.

IV. Case Study: Lake Skaneateles Watershed Program

The use of conservation contracts to achieve water quality objectives is becoming an increasingly popular policy tool [Johnson *et al.* 2001]. For example, the New York City Watershed Management Plan will spend $250 million on conservation contracting with private landowners in the Catskill-Delaware watershed over the next ten years to protect the City's water

[6] Using a conical hull approach, the estimated efficiency measures are the same under the radial output and input orientation, but their interpretation is different.

[7] If the landowner can change land attributes (e.g., reforestation), one could construct a different production unit (i.e., different output and input vectors) for each intervention and compare each parcel-intervention combination to every other parcel-intervention combination. With the exception of the case in which a single parcel may define the frontier under more than one of the available interventions, one simply ranks parcels under each parcel's most productive intervention. In the case of one parcel defining the frontier under more than one intervention, one would need to pick the frontier-defining parcel's most desirable state using other criteria.

supply and maintain its filtration waiver from the Environmental Protection Agency [NRC 2000: 213-239]. Examples of other contracting initiatives for water quality include North Carolina's $30 million Clean Water Management Trust Fund, Massachusetts's $80 million dollar effort to acquire riparian land to protect Boston's Wachusett Reservoir, and Costa Rica's $16 million per year effort to secure conservation contracts in, among other areas, the watersheds of municipal water supplies and hydroelectric dams.

In particular, scientists and policymakers have identified the establishment of vegetated riparian zones that protect surface waters from inputs of nutrients, pesticides, sediment and pathogens as an important policy for improving surface water quality [Tilman *et al.* 2001]. One such riparian buffer acquisition initiative is currently underway in upstate New York. The City of Syracuse (population 163,860) obtains its drinking water from Lake Skaneateles, which is outside of the City's regulatory jurisdiction. The 16 mile-long lake has a 60 square mile watershed that covers three counties, seven townships and one village. The population of the watershed is about 5000 residents, concentrated largely in the northern half of the lake where the City's intakes pipes are located. Land use is mainly a mix of forest (40 percent) and agricultural land (48 percent), on which cropping and dairy farming are most common.

The water from the lake is of exceptionally high quality and the City, using only disinfection by chlorination, meets drinking water standards without coagulation or filtration.[8] In recent years, however, the City has come under increasing pressure to consider filtration in order to satisfy the provisions of the Environmental Protection Agency's (EPA) Surface Water Treatment Rule. In 1994, the City signed a Memorandum of Agreement (MOA) with the New York State Department of Health that allows the City to avoid filtering water from the lake. The

[8] An estimated 20-65 million Americans drink unfiltered surface water [DeZyane 1990], including citizens in the cities of New York, Boston and San Francisco.

MOA requires that the City commit to a long-term watershed management program to reduce pathogen, chemical, nutrient and sediment loading into the lake. An important part of the management program is a conservation easement acquisition program through which up to $5 million will be spent over the next seven years (2001-2008) to secure easements on privately owned riparian parcels. By securing easements on riparian buffers in the watershed, the City hopes to avoid, or delay, the estimated $60-$70 million cost of a new filtration plant. The City wants to allocate its limited budget across the watershed in a way that will have the greatest effect on maintaining and improving water quality in the lake [Meyers *et al.* 1998].

In the analysis, we focus on prioritizing the acquisition of easements from an available population of 202 riparian parcels in the upper watershed of Lake Skaneateles (see Figure 3). Biophysical and economic data on these parcels were obtained from the Geographic Information Systems database of the City of Syracuse's Department of Water. The southwestern end of the lake is protected public land and is thus excluded from the analysis. Data on parcels in the southeastern end of the lake were not available at the time of analysis, but because these parcels are far from the City's intake pipes, excluding them will have only minor effects on the final results.

Benefit Data

The City wishes to reduce sediment, chemical, pathogen and nutrient loading into its water supply. Sophisticated hydrological models, however, are not available for the Lake Skaneateles watershed. To measure the contribution of each parcel to the City's water quality objectives, the City's Department of Water convened a scientific panel to help it develop a parcel-scoring system based on known land attributes in the watershed [Myers *et al.* 1998]. The panel developed two potential systems: an interval-scale scoring equation and a ratio-scale scoring equation. The equations, which are described in the appendix, are weighted linear functions of biophysical attributes and assign a score to each parcel; the higher the score, the higher the benefit from easement acquisition.

The panel identified five biophysical attributes that affect the City's water quality objectives (see appendix). These five attributes are combined in the linear scoring equations to generate a score, e_i, for each parcel that can then be used in the optimization approach in expressions [1]-[3]. We refer to this optimization approach as the *E-max* approach (for "environmental score maximization"). In the distance-function approach, which we will refer to as the *Nonparam* approach (for "nonparametric"), the five attributes are treated as outputs and cost (easement and transaction) is treated as a single input. We also derive easement portfolios under another parcel-scoring method for water quality objectives: the Parcel-Pollutant-Weighting (PPW) equation [Azzaino *et al.* 2002], which is described in the appendix.

Cost Data

A regional appraising company estimated that easements around Lake Skaneateles would cost between 40 percent and 60 percent of the assessed land value of a parcel [Gardner 2000]. In the analysis, we use 50 percent. A change in the percentage affects the number of parcels that can be acquired for a given budget, not the order in which the parcels are acquired. There were not enough observations on sales of properties with easements in the region to estimate a hedonic equation of easement costs. Based on transaction cost information from the local Finger Lakes Land Trust, we also assume that there is a transaction cost of $5000/easement.

V. Results

In this section, we examine two aspects of the performance of the distance-function approach: (1) the ways in which the *NonParam* portfolio differs from the portfolios derived using the *E-max* approach under the three parcel-scoring methods; and (2) the total parcel scores generated by the different portfolios when scored under each scoring method. The point of this latter exercise is to examine the robustness of the *NonParam* portfolio across plausible benefit measures; i.e., what would be lost if a conservation agent used the distance-function approach when, in fact, one of the scoring equations was the "true" measure of parcel benefits?

We begin with an exploration of the second aspect. For each scoring method, we calculate the total score generated by the parcel portfolio chosen using the conventional targeting approach embodied in expressions [1]-[3]; i.e., the *E-max* approach. A portfolio score is calculated at each of thirty-four budget levels, ranging from \$0 to \$11.8 million. The maximum budget level is equivalent to enough money to buy riparian easements across the entire upper watershed, given the assumed cost of contracting (i.e., $\sum_{i=1}^{202}(c_i + t_i)$). We refer to this amount as the Total Watershed Cost. We refer to the sum of all parcel scores under a given scoring method as the Total Watershed Benefit (i.e., $\sum_{i=1}^{202} e_i$). We also calculate the scores generated by the *Nonparam* portfolio at each budget level.[9]

Figure 4 illustrates the results for the interval-scale scoring equation. The x-axis represents the budget levels in percent of the Total Watershed Cost. The y-axis represents the environmental benefits achieved as a percentage of the Total Watershed Benefit. By definition,

[9] Eight parcels lie on the frontier and are equally efficient (θ =1), but these parcels cost only \$135,050, which is less than the first budget level used in the analysis. Thus there was no need to resort to other criteria to discriminate among the efficient parcels.

the *E-max* approach achieves the maximum score per dollar expended, and thus its curve is on the outside. The *Nonparam* portfolio curve tracks the *E-max* curve quite closely. For example, with a budget of about \$2.7 million, the *E-max* approach achieves 62% of the total watershed benefits, while the *NonParam* approach achieves 51%. Under a budget of about \$5 million, the *E-max* approach achieves 85% of the total benefits, while the *NonParam* approach achieves 84%.

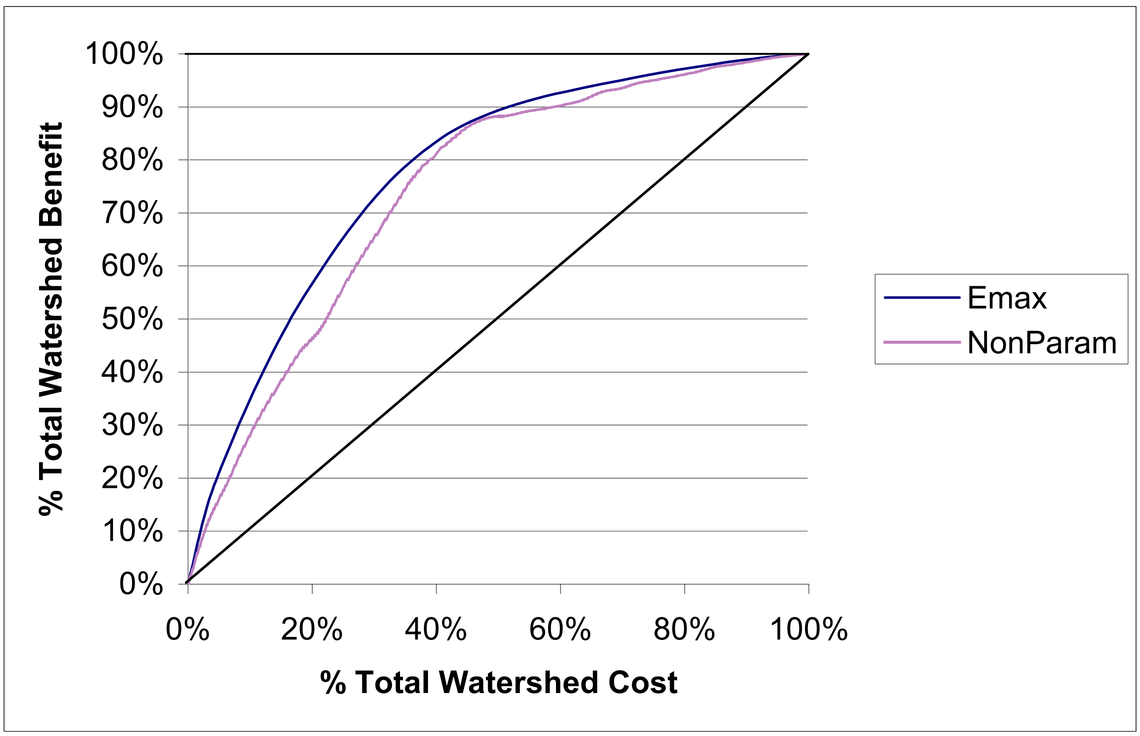

Figure 4 – Portfolio Performance (Interval-Scale Scoring Equation)

Rather than present the corresponding figures for each scoring method and then pick out specific budget points for illustrative purposes, we consider the performance differences between the two approaches by comparing the areas under the curves and above the 45° line in each figure [Babcock *et al.* 1996]. If *F(B)* is the fraction of the Total Watershed Benefit achieved with the expenditure of B, then one wants to calculate $A = \int_0^1 F(B)dB - \frac{1}{2}$. For each parcel-scoring method, we estimate an area equal to 2*A* by using trapezoids at each of the thirty-four budget intervals. The greater the difference between 2*A* under the *E-max* curve and the equivalent area under the *NonParam* curve, the greater the loss of efficiency if the parametric scoring-equation were accurate and one chose the *NonParam* portfolio rather than the *E-max* portfolio. The same areas are also calculated for the portfolios derived using the other scoring methods; e.g., the *E-max* portfolio selected using the ratio-scale equation is scored with the interval-scale equation and compared to the *E-max* portfolio selected using the interval-scale equation. This empirical exercise is similar to the exercise one might do when comparing parametric and nonparametric statistical tests; one wants to know the efficiency loss from choosing a nonparametric or erroneous parametric procedure when in fact the underlying population was of a particular parametric form.

The areas under the curves are listed in Table 1. The data in the table answers the question, "What if one were to choose a portfolio based on one benefit measure, when another benefit measure is more accurate?" For example, under the interval-scale scoring equation, the area under the *E-max* curve is 0.55, while the area under the *NonParam* curve is 0.48, indicating that there is about a 12% overall loss in efficiency if one were to choose the *NonParam* portfolio when, in fact, the interval-scale scoring equation is the correct way to measure parcel benefits. If, however, the interval-scale scoring equation were the most accurate way to measure benefits (Area = 0.55) but one instead chose the portfolio derived under the ratio-scale scoring equation (Area = 0.37), there would be a 33% overall loss in efficiency. By virtue of the distance-function approach's ability to achieve maximal attributes at minimal cost, the cost-efficiency of the *NonParam* portfolio is robust across scoring functions. In contrast, an *E-max* portfolio chosen under one scoring method may not remain cost-efficient if its parcels' true values are reflected best by another method.[10]

Table 1 – Portfolio Performances under Alternative Benefit Measures

Portfolio	*Areas Under Portfolio Curves in Benefit-Cost Space*		
	Interval-Scale	**Ratio-Scale**	**PPW**
Interval-Scale	0.55	0.57	0.47
% *E-max*	100%	87%	72%
Ratio-Scale	0.37	0.65	0.48
% *E-max*	67%	100%	74%
PPW	0.35	0.54	0.65
% *E-max*	64%	83%	100%
NonParam	**0.48**	**0.57**	**0.57**
% *E-max*	**88%**	**87%**	**87%**

More insights into the relative performances of the different portfolios can be obtained by comparing the desirable biophysical attributes secured by each portfolio at a given budget level. The City of Syracuse plans to spend \$1 - \$2.5 million dollars and then evaluate whether further easement acquisitions are required. For purposes of illustration, we choose a budget of \$2.5 million and summarize the portfolio characteristics in Table 2. The qualitative results are maintained over all budget levels (they are more dramatic as the budget approaches zero, and less dramatic as the budget approaches \$11.8 million). In each attribute category except one, the

[10] The interval-scale portfolio performs well when scored under the ratio-scale equation because (1) the parcel scores under each equation are strongly positively correlated ($\rho = 0.96$), and (2) the ratio-scale equation scores almost one-quarter of the parcels as zero (no benefit from an easement). These two factors make it relatively easy for the interval-scale portfolio to perform well when scored by the ratio-scale equation.

NonParam portfolio dominates the other portfolios. The parcels in the *NonParam* portfolio are farther on average from the City's water intake pipes.

Table 2 - Portfolio Characteristics

Budget = $2.5 million						
Portfolio	**Stream Exposure (ft.)**	**Total Acreage**	**Acres of HSL**	**Acres of 100-ft Buffer**	**Average Distance to Intake Pipes (miles)**	**Number of Parcels**
Interval-Scale	177,310	3034	1041	398	2.0	112.5
Ratio-Scale	185,509	3309	1134	422	1.8	86.9
PPW	179,741	3920	1092	417	2.0	71.0
NonParam	205,722	4112	1193	470	2.4	84.7
Maximum Possible	228,961	4204	1285	513	1.6 (minimum)	

The *NonParam* portfolio performs best in obtaining stream exposure, total acreage and acres of hydrologically sensitive land (HSL) and worst in obtaining nearby parcels because stream exposure, total acreage and acres of HSL are positively spatially correlated ($\rho \in [0.55, 0.72]$) and they are negatively correlated with distance to intake. Furthermore, the spatial variabilities of stream exposure, acres and acres of HSL are similar (Gini coefficients of 0.44, 0.59 and 0.41, respectively), while the spatial variability of distance to intake is higher (Gini coefficient of 0.65; i.e., more spatially concentrated).

Simulations with artificially generated landscapes of two biophysical attributes (see appendix for details) suggest that the *NonParam* portfolio performs best when correlations are positive and spatial heterogeneity is low, and that differences in spatial heterogeneity among the attributes have a greater effect on performance than do the correlations among attributes. When one attribute has low variability and another has high variability, the effects on distance-function performance are intensified: the distance-function portfolio performs even better in obtaining the low variability attributes and even worse in obtaining the high variability attributes. Given the moderate to high spatial variability of the desired biophysical attributes in the Lake Skaneateles watershed (which reduces the performance of the distance-function approach), the robust performance of the *NonParam* portfolio suggests that the distance-function approach to targeting conservation investments may perform equally as well in other conservation contexts.

VI. Other Advantages of the Distance-Function Targeting Approach

Despite decades of research on conservation targeting, mainly by biologists, Prendergast *et al.* observed that practitioners had not adopted sophisticated targeting methods. They argued that practitioners often have a "general antipathy toward what is seen as a prescriptive approach to conservation….(p.484)." The *E-max* approach in expression [1]-[3] tends to generate results that practitioners perceive as too prescriptive, and it does not allow practitioners to easily compare parcels relative to one another. The *E-max* approach generates rankings in units of parcel benefits divided by contract cost, a measure not easily interpreted when the parcel benefit is an artificial index. In contrast, the distance function approach generates rankings in terms of contract costs, which are more easily understood. Moreover, the concept of maximizing artificial index numbers is not easily communicated, whereas the concept of trying to obtain as many of the desirable biophysical attributes as possible given a fixed budget is clearer. Furthermore, the distance measures allow for more intuitive categorizations of parcels by comparing all parcels to a reference set of efficient parcels.

The distance function approach also has advantages in conservation initiatives like the Lake Skaneateles program, in which no mechanism exists to simultaneously elicit all landowners' offer prices for accepting a conservation contract on their land (e.g., a procurement auction). Conservation practitioners often use two cost discovery methods: (1) wait for a landowner to express interest in a conservation contract and then negotiate over the contract price (often the approach used by land trusts); or (2) estimate *ex ante* the likely willingness-to-accept of each landowner and then negotiate with landowners sequentially by parcel rank. Thus, practitioners need a way of assessing the implications of new information on contract costs without having to continually update and re-solve a programming model. We argue that the output from the distance-function approach is easier for practitioners to adapt in the field and will lead to more accurate conservation targeting.

Assume, for example, that the contracting budget is \$2.5 million and Parcel "002-04" is in both the *E-max* interval-scale portfolio and the *NonParam* portfolio. A riparian easement on the parcel is estimated to cost \$12,000. After negotiating with the landowner, the contracting agent discovers that the contract cost is higher than originally estimated. To consider the effect of a contract cost change in the *E-max* approach, the contracting agent must minimize the portfolio contracting cost subject to a portfolio total score target in order to derive the allowable increases and decreases in contract cost under which the current basis remains optimal. The minimization suggests that contract cost could increase by as much as \$15,985 without a change in the optimal basis.

Using the distance function approach, the contracting agent would know that Parcel 002-04 is 96% of the way to the frontier ($\theta = 0.96$). Through simple arithmetic,[11] the agent can calculate that if the contract cost of Parcel 002-04 were to increase by \$15,985, the parcel would shift to about 41% of the way to the frontier. In this case, ten other parcels that formerly were not part of the solution would have higher efficiency scores and would be considered preferable

[11] Divide the parcel's target cost of (0.96*\$12,000) = \$11,520 by the new contract cost of \$27,985.

to Parcel 002-04. When more than one contract cost changes, the ease with which relative rankings can be updated using the distance function approach is even more important.[12]

A nonparametric programming approach to targeting has the advantage that only the biophysical attributes of the landscape need be considered. Knowledge about the way in which the attributes combine to produce the desired environmental amenities is not needed. A priori knowledge about the relative importance of the different attributes in contributing to the environmental objective can, however, be incorporated into the nonparametric approach through constraints on the multipliers in [5]-[8], which are currently only restricted to be non-negative. Restrictions on the multipliers will alter the surface of the frontier and thus alter the estimated efficiencies of the parcels. Proposed techniques for implementing multiplier restrictions include placing upper and lower bounds on individual multipliers [Dyson and Thanassoulis 1988; Roll *et al.* 1991]; imposing bounds on the ratio of multipliers; appending multiplier inequalities [Wong and Beasley 1990]; and requiring multipliers to belong to given closed cones [Charnes *et al.* 1989, 1990].

VII. Conclusion

Policymakers and conservation practitioners throughout the world seek flexible tools to integrate spatially heterogeneous biophysical and economic data into cost-efficient conservation plans. In this paper, we recognize the difficulty associated in estimating the environmental amenities provided by a unit of land. We argue that there is often greater certainty about which

[12] This statement assumes that no parcel's price decreases enough to greatly transform the surface of the frontier. Such a transformation is most likely to occur with changes in contract costs for parcels found close to the frontier and near the area of increasing returns to scale on a convex hull over the data. It is in this area of the attribute-cost space that small absolute changes in contract costs can have a large impact on a parcel's relative position in attribute-cost space. The parcels in such areas can easily be identified *ex ante* through a modification of the original programming model.

biophysical land attributes contribute to supplying an environmental amenity than there is about the way in which these attributes combine to produce the amenity. Based on this observation, we introduce an alternative, nonparametric distance function-based method for incorporating biophysical and economic data to improve the targeting of conservation investments.

We empirically compare different conservation targeting approaches by using GIS data from a riparian easement contracting initiative in upstate New York. In this empirical application, we use data available to decision-makers, explicitly consider actual approaches used by decision-makers, and approach the problem at the geographic scale at which decisions are being made. We demonstrate that in the absence of a widely agreed upon specification for an environmental amenity function, policymakers may do well to consider a non-parametric distance function-based approach to conservation targeting. The land portfolios generated by the distance-function application have many desirable properties, including intuitive appeal, robust performance across plausible parametric amenity measures, and the generation of ranking measures that can be easily used and manipulated by field practitioners.

Although we apply the distance-function approach to the case of riparian land contracting for water quality objectives, the approach can be used for any conservation initiative. For example, conservation practitioners interested in habitat conservation may identify species diversity, habitat size, genetic dissimilarity indices of critical species, and distance from protected areas as key habitat attributes. The way in which these attributes combine to produce "habitat quality" is unknown. A reasonable conservation approach would thus be to maximize the joint output of these attributes subject to the cost of securing them.[13] Even in cases in which specific functional forms are known for key environmental objectives (e.g., a sediment loading

[13] Issues associated with substitutability and complementarity among parcels, however, may be complicated to incorporate into the distance-function approach without specifying all of the possible combinations. More research on this aspect of conservation investment targeting is needed.

model), the distance-function approach would be useful if there were more than one environmental objective that policymakers wanted to achieve (e.g., reduce pathogen, sediment and nutrient loading). A distance function approach also allows conservation agents to consider costs that may not be convertible into monetary units (e.g., undesirable changes in rural livelihood patterns).

Conservation targeting based on distance functions does not require decision-makers to reduce multiple biological dimensions into a single value. The approach therefore has a strong potential to make attempts to improve the cost-efficiency of conservation investments more attractive to decision-makers. Our analysis only describes a fraction of the full potential of the approach. We believe further analysis and application of distance-function targeting approaches is warranted and will lead to more effective conservation policy design.

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Appendix

A.1 Interval-Scale Scoring Equation

The interval-scale scoring equation developed by the City of Syracuse is:

Environmental Benefit Score (EBS) = .2 *Acreage* + .2 *Priority Zone* + .25 (*Distance to Intake*)$^{-1}$ + .25 *Acres of Hydrologically Sensitive Land* + .1 *Stream Length*

The attribute *Distance to Intake* measures the planametric distance from the geometric center of the parcel to a point exactly midway between the City's two water intake pipes. The closer to the pipes, the more desirable is the parcel of land. *Priority Zone* is a categorical variable, converted to a numeric scale, that captures the development potential and land use intensity of the zone in which a parcel is found. *Stream Length* is the length of the stream frontage (exposure) in each parcel, and *Acres of Hydrologically Sensitive Land* includes hydric soils, steeply sloped soil, wetlands and frequently flooded soils. Although acres of 100-foot wide riparian buffer are considered important to reducing pollutant loading, the area that is drained (*Acreage*) and the amount of exposure a parcel has to surface water (*Stream Feet*) are more important and are highly correlated with acres of buffer. The scientific panel therefore did not include acres of riparian buffer in the parcel scoring equation, but the attribute is important to the City's objectives.

The higher the parcel score, the more desirable the parcel is for water quality protection. In order that parcel attributes can be meaningfully compared to each other and that the units of measurement do not affect the scores, each attribute is scaled so that the least-favorable observed value generates a score of zero and the most-favorable observed value generates a score of one. For example, the smallest parcel in the data set was 0.17 acres, and thus this parcel received a standardized score of zero for the acreage attribute. The largest parcel was 136 acres and thus received a standardized score of one for the acreage attribute. Intermediate values receive a standardized score based on the relative position between the high and low values:

$$Interval - Scale\,Score_{ij} = \frac{OBS_{ij} - MIN_i}{MAX_i - MIN_i}$$

The standardized score of attribute i for parcel j, called an Interval-Scale Score, derives from subtracting the minimum observed value for the attribute from the observed value and dividing this number by the difference between the maximum and minimum values for attribute i.

A.2 Ratio-Scale Scoring Equation

The ratio-scale scoring equation uses the attributes found in the interval-scale equation, but its form and normalization differs:

Environmental Benefit Score (EBS) = 0.27 *Acreage* + .27 *Priority Zone*

- 0.27 *Distance to Intake* + .33 *Acres of Hydrologically Sensitive Land*

+ 0.13 *Stream Length*

Excluding the *Distance to Intake* weight, all the weights sum to one. Each parcel is then penalized for its distance from the intake (represented by a negative coefficient on *Distance to Intake*). All parcel scores are assumed to be greater than or equal to zero (a parcel that generates a negative score from the ratio-scale scoring function is scored as zero). Each attribute is scaled so that the most-favorable observed value generates a score of one and every other parcel is compared to that parcel; i.e., for the *j*th parcel and the *i*th attribute,

$$Ratio - Scale\,Score_{ij} = \frac{OBS_{ij}}{MAX_i}$$

A.3 Parcel-Pollutant-Weighting Model

The Parcel-Pollutant-Weighting Model is based on the approaches used by the New York State Department of Health [1999] and Hermans [1999] and is developed and explained in Azzaino *et al.* [2002]. We summarize the model briefly. Each parcel is assigned a land-use classification based on GIS data collected from New York's Real Property database. Based on this classification, the biophysical attributes of the land parcel (drainage area and distance to intake) and the results of a published water quality study [New York State Department of Health 1999], each parcel's potential loading of phosphorus and pathogens is assessed qualitatively. This qualitative assessment is then assigned an index number ranging from 10, for a qualitative assessment of "high," to 3.33, for a qualitative assessment of "low." If a parcel is acquired for the riparian buffer easement, a percentage reduction in pollutant loading is assumed, based on the current qualitative assessment and data in Hermans [1999: 136]. Equal weights are used on reductions in pathogens and phosphorous loadings.

A.4 Easement Acquisition Problem – additional characteristics

The maximization problem is

$$\max_{p_i,\lambda,\mu_1,\mu_2} L = \sum_i p_i\, e_i + \lambda (D - \sum_i p_i\,(c_i + t_i)) + \mu_1 p_i + \mu_2 (1 - p_i) \qquad \text{[A1]}$$

This formulation is equivalent to ranking parcels from highest to lowest based on their *e*/*c* ratio and accepting contracts until the budget is exhausted. One can interpret λ^* as a shadow value at the optimum denoting the increase in environmental quality associated with an increase in the budget constraint. When one allows partial parcel contracting, one generates a positive shadow value for all budgets less than the total contract value of the available parcels.

Complementary slackness requires that:

$$p_i^* = 1 \; when \; e_i > \lambda^*(c_i + t_i) \quad \text{(parcel is contracted)} \qquad [A2]$$

$$p_i^* = 0 \; when \; e_i < \lambda^*(c_i + t_i) \qquad [A3]$$

$$p_i^{*\lambda} \in [0,1] \; when \; e^{\lambda}{}_i = \lambda^*(c_i^{\lambda} + t_i^{\lambda}) \qquad [A4]$$

$$where \;\; p_i^{*\lambda} = \frac{D - \sum p_i^*(c_i + t_i)}{(c_i^{\lambda} + t_i^{\lambda})}$$

In other words, if one unit in parcel *i* is valuable enough to be acquired, every other unit in parcel *i* is good enough to be contracted (by the parcel homogeneity assumption). One parcel, $p_i^{*\lambda}$, may end up with a partial contract because budget constraints prevent contracting on every acre in the parcel. The shadow value, $\lambda^* > 0$, is the threshold ratio of environmental benefits to contract cost ($e^{\lambda}{}_i/c^{\lambda}{}_i$) that indicates which parcels are contracted and which are not. One also knows that $\frac{\partial \lambda^*}{\partial D} < 0$ and that $1/\lambda^*$ is the unit price of the environmental amenity (i.e., a unit of environmental benefit score) if there existed a uniform-price market for water quality in the Lake Skaneateles watershed. In such a market, the City of Syracuse would pay $(1/\lambda^*)\ \Sigma\ p_1e_1$ for its contracted land portfolio.

A.5 Conical Hull versus Convex Hull Programming Approaches

The convex hull approach allows analysts to discriminate between technical inefficiency and scale inefficiency by allowing supporting hyperplanes to pass through any point on the axes, whereas the conical hull approach in [5]-[8] forces all hyperplanes to pass through the origin. A conical hull approach is equivalent to assuming that the production technology exhibits constant returns to scale. Clearly each parcel in the analysis is a unique production unit that could not be replicated, as in the typical understanding of constant returns to scale. Trying to make comparisons between firms and land parcels, however, is misleading. We are interested in the most productive parcels. Since the conical hull frontier envelops a larger feasible region than the convex hull frontier, parcels on the conical hull frontier are more productive than parcels found only on the convex hull frontier. If a convex hull approach to estimating the frontier were used, inefficient parcels are only compared to parcels of similar size. This inherent characteristic of the piecewise linear, variable returns-to-scale convex hull approach can lead to situations in which parcels that are less productive are ranked higher for targeting than more productive parcels. In the context of conservation targeting, the parcels closest to the estimate frontier must be the most productive parcels; otherwise one could generate a land portfolio that could be dominated by convex combinations of less efficient parcels (thus contradicting the original ranking).

A.6 Simulations with Artificial Landscapes

We assume that there are two biophysical attributes of interest, A and S. Let A denote the per-parcel acreage measure, $A_0 \leq A \leq A_1$, and S denote the per-parcel stream exposure measure, $S_0 \leq S \leq S_1$. Denote the joint density function of A and S that is available for contracting as *f*(A,S). This joint density function can be used to measure the share of land on a given landscape with certain attributes. For example, the share of land with $A_M \leq A \leq A_Z$ is given by $\int_{S_0}^{S_1}\int_{A_M}^{A_Z} f(A,S)\,dA\,dS$. The per-parcel cost is C, $C_0 \leq C \leq C_1$. In the simulation, we focus on the characteristics of *f*(A,S); namely the spatial correlation and concentration of A and S across the landscape. We generate artificial data sets to use in numerical analyses. We specify marginal density functions for A and S and allow the variability of each to vary. We use a standard beta distribution with parameters *p* and *q* for the marginal distributions. The beta distribution allows one to vary the relative variability of the marginal distributions: high *p* and *q* correspond to lower spatial variability; $p > q$ skews the distribution and reduces the relative variability. Using a technique developed by Johnson and Tenenbein [1981] and applied by Babcock *et al.* [1997], we add correlation, ρ, to the marginal distributions and draw correlated A and S observations from the marginal distributions. We then define different combinations of *p*, *q* and ρ, where each combination represents a landscape with a given *f*(A,S). We then generate 2,000 random correlated draws for each combination. The distribution of costs per parcel, which is held constant across all landscapes, has a low-variance density (p=q=50) and mild positive correlation with A and S in all landscapes. As in Section V, the distance-function (*Nonparam*) portfolio is derived under thirty-four budget levels. The performance of the distance-function portfolio over all budget levels is then compared to the performance of the portfolio that maximizes the acquisition of that attribute (i.e., an analysis similar to that presented in Table 1). Thus, for example, on a landscape where A and S are positively correlated (ρ = 0.3) and the variability of A on the landscape is low (p=q=50) and the variability of S is high (p=q=0.50), the distance-function portfolio is 99.78% as efficient in obtaining the attribute A as the portfolio selected to maximize the acquisition of A.

Table A1 – Performance of Distance-function Portfolio as a Percentage of the Maximum Total Amount of A and S Available

Landscape	A	S
ρ = +0.3_pA=50_qA=50_pS=0.5_qS=0.5	99.78%	78.90%
ρ = 0_pA=50_qA=50_pS=0.5_qS=0.5	99.60%	77.58%
ρ = 0_pA=50_qA=50_pS=50_qS=50	99.58%	99.20%
ρ = +0.3_pA=50_qA=50_pS=50_qS=50	99.57%	99.57%
ρ = +0.3_pA=50_qA=50_pS=50_qS=11.9733	99.39%	99.86%
ρ = -0.3_pA=50_qA=50_pS=11.9733_qS=50	99.34%	96.40%
ρ = -0.3_pA=50_qA=50_pS=50_qS=11.9733	99.32%	99.64%
ρ = +0.3_pA=50_qA=50_pS=11.9733_qS=50	99.03%	98.79%
ρ = -0.3_pA=50_qA=50_pS=50_qS=50	98.86%	99.67%
ρ = -0.3_pA=50_qA=50_pS=0.5_qS=0.5	98.52%	83.09%
ρ = +0.3_pA=0.5_qA=0.5_pS=0.232051_qS=0.5	93.44%	81.77%
ρ = +0.3_pA=0.5_qA=0.5_pS=0.5_qS=0.5	88.76%	90.48%
ρ = 0_pA=0.5_qA=0.5_pS=0.5_qS=0.5	87.09%	84.72%
ρ = +0.3_pA=0.5_qA=0.5_pS=0.5_qS=0.232051	83.36%	94.92%
ρ = -0.3_pA=0.5_qA=0.5_pS=0.5_qS=0.5	82.73%	82.19%
ρ = -0.3_pA=0.5_qA=0.5_pS=0.5_qS=0.232051	78.43%	89.81%
ρ = +0.3_pA=0.5_qA=0.5_pS=50_qS=50	77.61%	99.62%
ρ = 0_pA=0.5_qA=0.5_pS=50_qS=50	76.77%	99.68%
ρ = -0.3_pA=0.5_qA=0.5_pS=50_qS=50	76.55%	99.46%